An introduction to deep generative modeling

Abstract

Deep generative models (DGM) are neural networks with many hidden layers trained to approximate complicated, high■dimensional probability distributions using samples. When trained successfully, we can use the DGM to estimate the likelihood of each observation and to create new samples from the underlying distribution. Developing DGMs has become one of the most hotly researched fields in artificial intelligence in recent years. The literature on DGMs has become vast and is growing rapidly. Some advances have even reached the public sphere, for example, the recent successes in generating realistic■looking images, voices, or movies; so■called deep fakes. Despite these successes, several mathematical and practical issues limit the broader use of DGMs: given a specific dataset, it remains challenging to design and train a DGM and even more challenging to find out why a particular model is or is not effective. To help advance the theoretical understanding of DGMs, we introduce DGMs and provide a concise mathematical framework for modeling the three most popular approaches: normalizing flows, variational autoencoders, and generative adversarial networks. We illustrate the advantages and disadvantages of these basic approaches using numerical experiments. Our goal is to enable and motivate the reader to contribute to this proliferating research area. Our presentation also emphasizes relations between generative modeling and optimal transport.